Human-Computer Interaction in Artificial Intelligence for Blind and Vision Impairment: An Interpretative Literature Review Based on Bibliometrics

L'interaction humain-machine en intelligence artificielle pour les aveugles et déficients visuels : Une revue de littérature interprétative fondée sur la bibliométrie

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The rise of artificial intelligence and particularly machine learning conduct to an emerging landscape of intelligent interactive systems. Such technologies help clinicians to detect diseases from medical imaging, and allow to describe the visual world to people with visual impairment. However, this new technological landscape comes with a set of HCI challenges. To better understand the importance of HCI in AI, we focused on blind and vision impairment as a representative application domain. Using bibliometric techniques, we retained 187 scientific publications organized in three clusters. Our findings show that HCI is absent in research related to medical computer systems but has moderate importance when the aim is to assist BVI in their daily life.

CCS Concepts: • **General and reference → Surveys and overviews**; • **Computing methodologies → Artificial intelligence**; • **Human-centered computing → Human computer interaction (HCI)**.

Additional Key Words and Phrases: Human-Computer Interaction, Artificial Intelligence; Visual Impairment; Blind; Review; Bibliometrics

L'essor de l'intelligence artificielle (IA) et en particulier du machine learning a conduit l'émergence d'un paysage de systèmes interactifs intelligents. Ces technologies aident les cliniciens à détecter des maladies à partir de l'imagerie médicale et permettent de décrire le monde visuel aux personnes déficientes visuelles. Cependant, ce nouveau paysage technologique est accompagné d'une série de défis en matière d'Interaction-Humain Machine (IHM). Pour mieux comprendre l'importance de l'IHM dans l'IA, nous nous sommes concentrés sur la déficience visuelle en tant que domaine d'application représentatif. En utilisant des techniques bibliométriques, nous avons retenu 187 publications scientifiques organisés dans trois clusters. Nos résultats montrent que l'IHM est absente des recherches liées aux systèmes informatiques médicaux, mais qu'elle a une importance modérée lorsque l'objectif consiste à assister les déficients visuels dans leur vie quotidienne.

Mots-clés additionnels : Interaction-Humain Machine ; Intelligence Artificielle ; Déficience Visuelle ; Revue ; Bibliométrie

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1 INTRODUCTION

The field of artificial intelligence (AI) has developed very rapidly in recent years, with exponential gains in data sizes, compute power, algorithms, and machine learning (ML) methods [5]. This conducts to an emerging landscape of rapid technological evolution towards more intelligent interactive technologies [32]. For example, deep learning (DL) as the underlying technology for computer vision gives opportunities to help clinicians detect diseases from medical imaging [17], or to serve visual understanding [9]. However, this new technological landscape comes with a set of challenges regarding health and accessibility [32]. Human–computer interaction (HCI) as a discipline, which focuses on the relationship between humans and technology, is called upon to address these challenges [32]. Moreover, there is a need to gain an understanding of areas for collaboration between the HCI and AI communities [30]. In this paper, we aimed the answer the following research question: *To what extent is HCI central in AI related to BVI?* We focused on blind and vision impairment (BVI) because vision is the most dominant of the five senses and plays a crucial role in every facet of our lives [43], such disability most interested HCI researchers within accessibility[18], and deep learning (as a subfield of machine learning) is used to describe the visual world [9, 14]. In this way, this paper presents the related works, the research methodology, and the preliminary results of an interpretative literature review grounded on bibliometrics concerning HCI in AI related to BVI.

2 RELATED WORK

To better understand the relations between HCI, AI, and BVI, we search for review papers interested in HCI and AI, AI for BVI, and AI for BVI in a HCI context. Firstly, questioning AI in HCI or the opposite is not new. During the last 20 years, many studies investigated the relations between both fields (see Winograd [42], Lieberman [16], Spaulding [30], and Grudin [8]). As stated by Lieberman, *"The AI community needs to pay more attention to HCI issues, rather than just concentrate on algorithms and leave the interface until later. [...] while HCI community needs to get over its paralyzing fear of AI failures and take a hard look at the opportunities for making interfaces more intelligent."* [16]. Usable AI [8] and Human-Centered AI [28] are typical topics trying to join HCI and AI. Recent contributions developed methods and practical tools mainly about ML and HCI and *vice versa* [5], as well as frameworks considering high levels of human control *and* automation [28].

Secondly, AI in healthcare is a hot topic [11, 17]. AI can effectively support clinicians by taking care of trivial tasks, empowering humans towards enhanced performance and attainment of higher goals [32]. Liu et al. [17] provided the first systematic review on the diagnostic accuracy of DL algorithms versus healthcare professionals using medical imaging. They highlight that most studies assessed DL diagnostic accuracy in isolation, while very few reported comparisons with clinicians [17]. Finally, real-world clinical implementation has not yet become a reality [11].

Thirdly, numerous researchers introduced the use of AI to help BVI [4, 33]. Bhowmick and Hazarika [4], which reviewed assistive technologies for BVI, presented sensory substitution, computer vision, and navigation/wayfinding as trendy research topics. Regarding the third one, Tapu et al. [33] concluded that ML-based computer vision is still far from approaching the human capability to understand the semantic within environments.

Despite the extensive work on AI and HCI, the relations between both fields remain underinvestigated and particularly when the focus is placed on a subfield of research. To the best of our knowledge, no study gives an overview about the place of HCI in AI for BVI.

3 RESEARCH METHOD

In this paper, we performed an interpretive literature review guided by a bibliographic coupling analysis. Combining an interpretative literature review with bibliometrics can be illustrated by the flesh and bones metaphor, whereby researchers' interpretation of documents (the flesh) is added on the top of the field structure (the bones) revealed by a bibliometric analysis [36]. Bibliometric techniques introduce some objectivity into the classification of the publications of a research field [36]. More specifically, we applied the documents bibliographical coupling analysis (DBCA). If two documents cite the same third document, it means they are bibliographically coupled. The more two documents share bibliographic references, the stronger their relationship is. Hence, bibliographic coupling can be seen as a measure of document similarity [13]. DBCA is particularly helpful to comprehend the intellectual structure of a recent or emerging literature [45]. Moreover, bibliographic coupling could be combined with clustering methods to group similar nodes [13, 39].

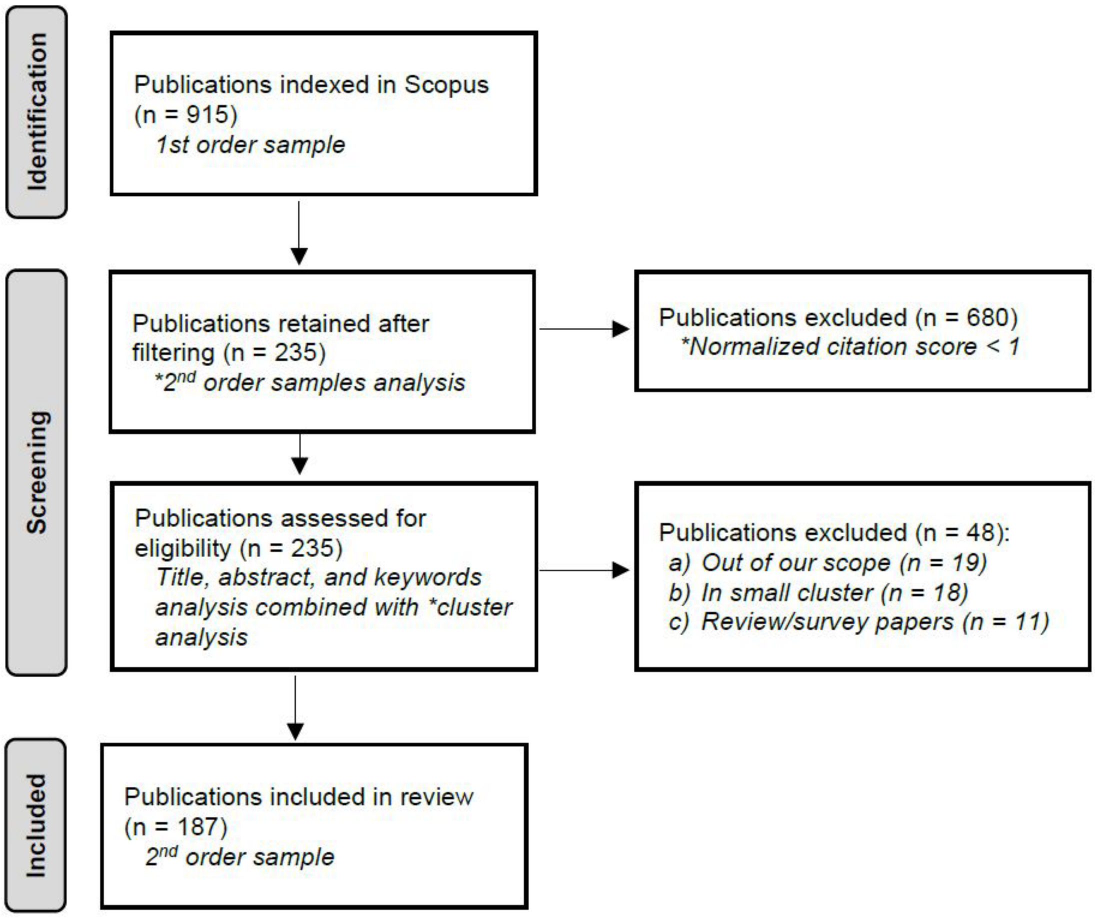

Fig. 1. Flow Diagram [21]. The (*) denotes that the processing have been supported by ARTIREV.

3.1 Data Collection and Cleaning

On the 4th of January 2022, we actualized the following query initially launched on the 15th of November 2021 on Scopus: *TITLE-ABS-KEY (("artificial intelligence" OR "machine learning" OR "deep learning") AND ("vis* impair*" OR blindness OR "blind people" OR "low vision")) AND DOCTYPE ("ar" OR "cp") AND SRCTYPE ("j" OR "p") AND SUBJAREA*

("COMP") AND PUBYEAR > 2015 PUBYEAR < 2022 AND LANGUAGE ("English"). We included different terms to denote BVI, and intentionally excluded the term "blind" because a lot of results were out of our scope (e.g., "blind-peer review"). We search for AI and particularly statistical learning approaches (i.e., ML and DL) because they received a considerable attention in recent years. Moreover, such technologies can benefit BVI in different ways (directly through assistive technology or indirectly through medical imaging analysis). We limited our search to publications that a) are a journal article or a conference proceeding, b) spanned the years 2016-2021 (included), b) are written in English, c) are classified in computer science, since HCI is categorized in that field. Using this query, we obtained a first-order sample of 915 documents citing 26'374 unique references.

Because scientific meta-databases contain significant data quality problems [6], we used ARTIREV to merge similar references [37]. Using fuzzy string similarity algorithms, we curated 28,2% of the cited references and obtained a final set of 18'949 unique references to perform the DBCA.

3.2 Data Analysis and Visualization

To retain our second-order sample, we compared multiple bibliographic coupling analyses and their corresponding science mappings at the following normalized citation thresholds: 0, 1.0, 1.5. A citation count normalized by a yearly mean citation takes into account the increasing citation count over time to not only retain the most cited documents. In that sense, a document with a normalized citation score higher than one denotes that it is more cited than others published in the same year. We retained the analysis at the threshold of 1.0 because it included sufficient documents (n = 235), and most of the intellectual structure at this threshold was the same as the one corresponding to the entire network. We used the association strength normalization and the Leiden algorithm clustering methods to produce the co-occurrence network and the corresponding map (resolution=0.5, other parameters as default) [34, 39]. This analysis provided seven clusters, four of which were small (< 10 documents). To produce the science mapping, we used the VOS mapping technique provided by VOSviewer [35].

Then, we analyzed the title, abstract, and keywords of the 235 documents. We excluded from this set: the documents within isolated or small clusters, those out of our scope (e.g., about diabetes), and misclassified review or survey papers even if they were related to our topic of interest. Also, we manually verified the cluster of each document and performed a change if necessary. At the end of this qualitative analysis, we retained a set of 187 documents classified within three main clusters. The database is available upon request.

To better understand the intellectual structure of each cluster, we analyzed the top five words frequencies with the top five most cited publications. To perform word count frequencies, we preferred ngram (bigram and trigram) to a unique word count because our subject contains numerous compound words. We also used English stopwords, created a custom stopwords list including frequent noisy terms in abstracts (e.g., *ltd*), and used the WordNetLemmatizer. We implemented the entire process on top of the NLTK Python library. In a second step, we focused on our research question. We coded each retained publication according to one of the three following system levels: a) software systems emerge from hardware systems and are based on information level, b) an HCI system denotes a person using IT, while c) a socio-technical system is related to a group, an organization, a community, or a society [41].

4 PRELIMINARY RESULTS

The VOS map shows 235 connected documents, while 187 of them are organized within three main clusters (see Figure 2). Publications within clusters were published between 2016 to 2021, with an average of about mid-2019. We found no temporal difference related to clusters.

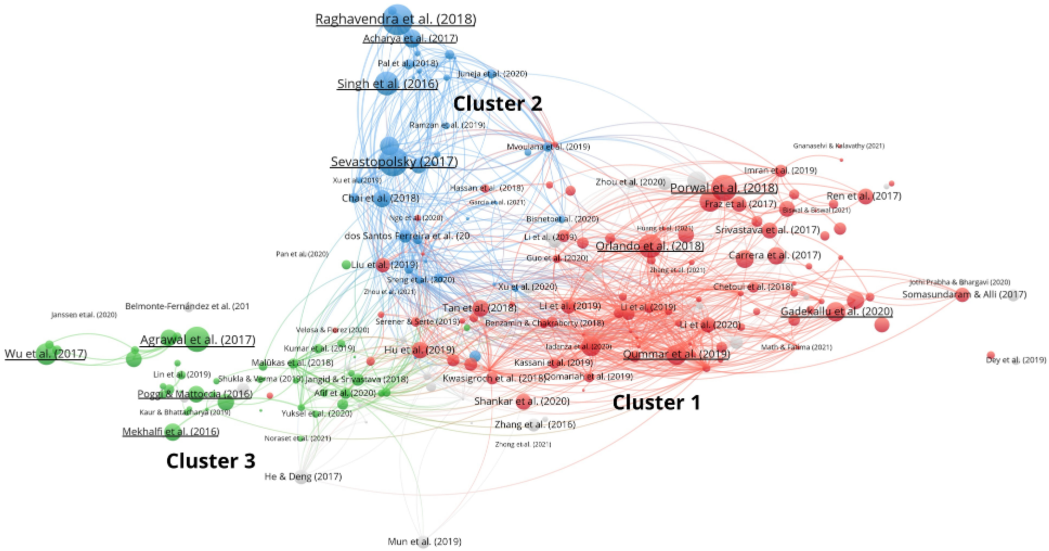

Fig. 2. Science mapping of AI related to BVI. A total of 235 are represented, 187 documents are clustered, and the remaining grey nodes are excluded from the analysis. The node size corresponds to the citation count. Documents selected for cluster analysis are underlined if possible.

Table 1. Frequency of the Top 5 Bi and Tri grams per Cluster.

Cluster 1		Cluster 2		Cluster 3	
Words	Frequency	Words	Frequency	Words	Frequency
diabetic retinopathy	161 (1.65%)	fundus image	39 (0.93%)	visually impaired	47 (0.95%)
fundus image	79 (0.81%)	deep learning	32 (0.77%)	deep learning	31 (0.63%)
neural network	58 (0.60%)	optic disc	24 (0.57%)	visually impaired people	21 (0.42%)
deep learning	56 (0.57%)	neural network	24 (0.57%)	blind people	18 (0.36%)
blood vessel	42 (0.43%)	glaucoma screening	18 (0.43%)	neural network	18 (0.36%)

4.1 Cluster Analysis

Cluster 1: Deep Learning Image Analysis for Retinal Diseases Diagnosis. This cluster (n=100) is comprised of publications that use DL to help the diagnostic of retinal diseases such as diabetic retinopathy, macular degeneration, or macular edema. More specifically, DL techniques are used to analyze fundus images and detect retinal lesions (e.g., microaneurysms, hemorrhages, exudates). The word frequency analysis shows that this cluster is related to a software system (see Table 1).

Publications selected for cluster analysis focused on object detection in fundus images, and the classification of such images to detect diabetic retinopathy. Studies improved state-of-the-art methods by: performing dimensionality reduction [7], classifying different stages of diabetic retinopathy [25], combining deep learned and domain knowledge (manually engineered) features [20], as well as combining exudates, optic disc, and vessel detection [24]. Deep convolutional neural networks (CNN) are mostly used [20, 24, 25]. Finally, datasets aim to help the development and evaluation of image analysis algorithms (e.g., Indian Diabetic Retinopathy Image Dataset [23]).

Cluster 2: Deep Learning Image Analysis for Glaucoma Detection. Similar to cluster 1, documents in this cluster (n=39) aim to help diagnose, screen, and detect glaucoma using DL for image analysis. The word frequency analysis shows that this cluster is related to a software system (see Table 1). Publications selected for cluster analysis improved previous algorithms using deep CNN [26], wavelet features of segmented optic disc [29], automatic optic disc and cup segmentation with better accuracy [40] or prediction time [27], as well as using features from texton and local configuration pattern [1]. CNN are also commonly used [1, 26, 27, 40].

Cluster 3: Deep Learning within Assistive Technology for BVI. This cluster (n=48) refers to different applications of DL (e.g., object detection, recognition, or navigation) to assist BVI in their daily life. Two primary lines of research, which can be differentiated by the contexts of use, are represented. The word frequency analysis shows that this cluster is related to an HCI system (see Table 1).

Firstly, researchers developed computer vision algorithms to describe the visual world to BVI. For instance, a complete model for visual question answering uses a diverse set of AI capabilities such as computer vision, natural language processing, and commonsense reasoning (see Agrawal et al. [2]). Given an image and an open-ended, natural language question about the image, the model provides an accurate natural language answer. Moreover, an automatic alt-text generator, which takes as input faces, objects, and themes from photos, target blind and screen reader users (see Wu et al. [44]).

Secondly, several systems aim to *recover* the sight to BVI in an indoor/outdoor navigation context. Researchers developed chest-mounted systems with advanced computation such as 3D computer vision, machine learning, or real-time pathfinding (see Poggi & Mattoccia [22], Mekhalfi et al. [19], and Li et al. [15]). Such systems combine navigation and recognition capabilities to move autonomously and to recognize objects. They provide different computer to human modalities such as haptic (e.g., via smartphone, cane), and/or speech.

4.2 The Centrality of HCI in AI related to BVI

The VOS density map highlights 187 publications related to their system level (see Figure 3). Out of 187 publications, 167 (89.3%) are related to a computer system, 29 (10.2%) are related to an HCI system, and one publication refers to a socio-technical system (0.5%). The highest density is visible in the software system part.

Software First in AI for Visual Disease Detection. The 139 publications within clusters 1 and 2 are related to the diagnosis, screening, and detection of leading causes of vision impairment. In addition, publications aim to treat a disease using DL for image analysis. Works in these clusters are mainly related to data collection, processing, modeling, and evaluation, with considerable attention on model optimization (e.g., focused on machine learning metrics). Although there is a strong motivation to help clinicians, we found no study investigating medical software in use. However, some studies compared clinicians' knowledge to an algorithm (see Islam et al. [12]).

Moderate importance of HCI in AI for BVI Assistance. The 48 publications within the third cluster aim to cope with a vision impairment. However, 29 (60.4%) are *solely* motivated to assist BVI and primarily focused on a software system in the form of a machine learning model. Moreover, due to the importance of navigation systems, the links between software and hardware is frequent. The remaining 18 publications (37.5%) are related to HCI, which includes BVI in different software development phases (see [31, 44]). We also noticed that HCI methods are used in technical research fields, such as computer vision or sensors/wearables. Finally, one publication (2.1%) is related to a socio-technical system (see Bennett et al. [3]).

Open Research Gaps. BVI is not yet the place when AI and HCI meet. We believe that AI needs more HCI than one currently finds [10]. AI applied to BVI healthcare seem to follow the computing evolution, which implies this

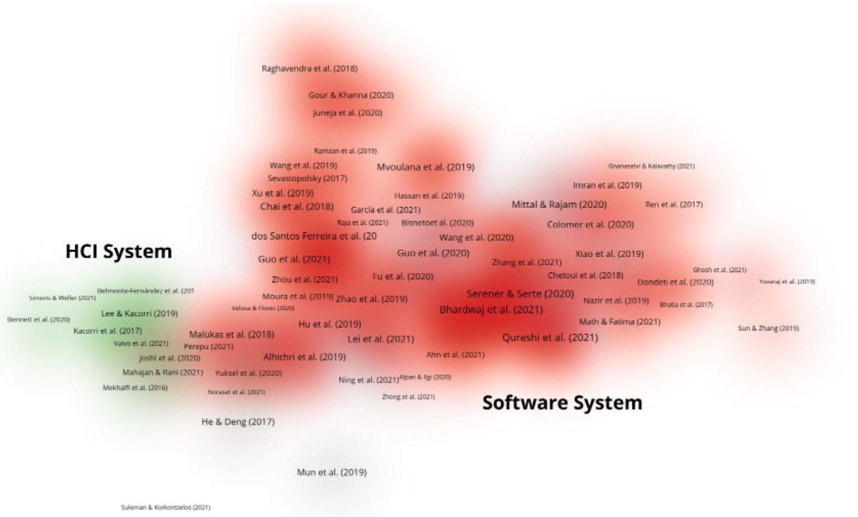

Fig. 3. Density Map of HCI in AI related to BVI. 187 documents are colored corresponding to their system. The density corresponds to the total link strength.

requirements hierarchy: *"If the hardware works, then software becomes the priority; if the software works, then user needs become important; and if user needs are fulfilled, then social requirements arise."* [41]. The absence of HCI can be explained by the lack of real-world clinical implementations [11] and the history that has shown that *"HCI has focused on technologies as they approach widespread use."* [8]. However, we suggest to the HCI community to explore transparency and explanation of AI systems [16], as well as medical staff and technology relationships (e.g., human augmentation, AI dependence) [32] even in a predictive way. Regarding AI-powered assistive technology, HCI and AI communities should work together to understand BVI people's behaviors better [32]. Although solution-oriented datasets exist [2, 44], data about BVI people using technology are missing. Such data will help find interaction patterns and better describe the issues they encounter in different contexts of use.

5 NEXT STEPS

In this paper, we aimed to understand the importance of HCI in the context of AI applied to BVI. To do so, we combined an interpretative literature review with the bibliographic coupling of documents. Our findings show that computer vision with deep learning is latent in the whole subfield of research, and it connects HCI and AI. However, HCI is not yet widespread in the AI community working on BVI. Researchers that developed AI-based medical systems did not include HCI, while HCI has moderate importance in assistive technologies.

Regarding the limitations, this preliminary study highlights the most important themes, but excludes less representative ones. Also, other threads of HCI research that appear in human factors and ergonomics, management of information systems, and information science [8] (i.e., not classified in computer science) are not considered. To investigate the links between HCI and AI in-depth, we recommend further investigations of assistive technologies using AI for BVI. To overcome the use of Scopus as the unique data source, we recommend using Web of Science in combination. This research could also benefit from a complete set of bibliometric techniques coupled with grounded theory (BIBGT) [38]. Understanding the schools of thought could be performed with a reference co-citation analysis, while a systematic analysis could follow grounded theory methods. Finally, a research organizations' science mapping can highlight the links between AI and HCI communities.

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